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~~ARRANGEMENT FOR PREDICTING AN ABNORMALITY OF A SYSTEM AND FOR IMPLEMENTING AN ACTION OPPOSING THE ABNORMALITY~~

INS A_1

The invention is directed to an arrangement for predicting an abnormality of a system and for the implementation of an action opposing the abnormality.

Description of the Related Art

The determination of an information flow of a system is known from ~~[1] and/or [2].~~ INS A_2.

The information flow described in these references characterizes a loss of information in a dynamic system and describes decaying statistical dependencies between the entire past and a point in time that lies p steps in the future as a function of p. Among other things, the utility of ~~the~~ such an information flow is ~~comprised therein~~ that a dynamic behavior of a complex system can be classified, ~~this leading thereto that~~ allowing a suitable parameterized model ~~is~~ to be found that enables a modelling of data of the complex dynamic system.

A neural network and the training of a neural network are known from ~~[3].~~ INS A3

Summary of the Invention

The object of the invention is ~~comprised in specifying~~ to provide an arrangement that, ~~first,~~ enables a prediction of an abnormality of a system and then implements an action opposing the abnormality.

~~This object is achieved according to the features of patent claim 1.~~ INS A4

An arrangement for predicting an abnormality of a system and for implementing an action opposing the abnormality is inventively recited ~~. A~~ that has a measured data pick-up ~~is provided therein~~ that determines measured data of the system. A processor ~~unit is configured such that~~ implements the following steps ~~are implemented:~~

(1) a neural network is trained on the basis of the measured data;

(2) the information flow of the system is ~~employed in order~~ used to make a prediction about anticipated measured data;

(3) when the prediction indicates that the abnormality of the system is anticipated, the action is implemented;

~~an~~ An actuator that implements the action is ~~thereby provided dependent~~ INS A5 on the respective application.

Ins B1

A goal of the invention is to provide a systematic approach to the general problem ~~and~~, ins ~~As a solution of this general problem derived therefrom, the determination of a quant~~ity (referred to below as prediction quantity) that is suitable for predicting dynamic events of a system. The early recognition of a pattern that represents abnormality in ~~an attack on~~ a "normal" behavior of the system is of great significance, as, among other things, the following applied examples document.

The applied strategy is divided into *three* steps:

1. The dynamically characterizing features of the system are extracted and adaptively learned (trained). The measure for learning the dynamics of the system in this dynamic learning phase should be general enough ~~adequately general in order~~ to correspond to stationary as well as non-stationary conditions. The dynamic learning phase is also used in order to demarcate a normal condition of the system from an abnormal condition (abnormality).
2. At least one variable (prediction quantity) is determined with which the abnormality is successfully described.
3. As soon as an occurrence of the abnormality is indicated, the information of the impending abnormality is used in order to oppose the impending abnormality via an actuator whose job is to restore the dynamic system into the normal condition. one also considers ~~It is thereby to be taken into consideration~~ that the normal condition is subject to a natural modification over the course of time, this is ~~this being~~ taken into consideration by adaption, i.e., continued training of the neural network, even after the learning phase.

One development endlessly loops through ~~is comprised therein that the~~ steps (2) and (3) of the processor unit ~~form an endless loop~~.

Another development of the invention deals all the situation where ~~comprised therein that~~ the predetermined abnormality is an information flow with a dynamic value below a prescribable threshold. In this case, the action can be comprised of ~~comprised in~~ supplying the system with noise. It is possible to deliver this noise ~~the noise~~ on the basis of a corresponding electrical field or a corresponding magnetic field. Both the electrical field as well as the magnetic field can ~~thereby~~ be supplied to the system using ~~on the basis of~~ at least one electrode.

An additional improvement ~~is comprised therein that~~ deals w/ a situation where the predetermined abnormality is an information flow having a dynamic value above a predetermined threshold. INS An ~~Reaction thereto can be such that the system is excited with a regular signal. This can~~ ensue using ~~on the basis of~~ an electrical or magnetic field. The electrical field and/or the magnetic field can be respectively supplied to the system on the basis of at least one electrode.

In the framework of another development, it is also possible to utilize an electrical and a magnetic field in combination in order to oppose the abnormality.

INS A6 ~~Developments of the invention also derive from the dependent claims.~~

Brief Description of the Drawings

Exemplary embodiments of the invention are presented in greater detail on the basis of the following Figures.

~~Shown are:~~

Figure 1 is a block diagram showing an arrangement for predicting an abnormality of a system and for implementing an action opposing the abnormality;

Figure 2 is a block diagram showing an actuator AKT2 ~~at~~ an active component, composed of a computer R, an interface IF, an energy store BT and two electrodes EL1 and EL2;

Figure 3 is a flowchart showing steps of a method for ~~the~~ implementation on a processor unit.

Description of the Preferred Embodiments

Figure 1 shows an arrangement for predicting an abnormality of a system and for implementing an action opposing the abnormality.

The measured data pick-up MDA registers measured data of a system S. To this end, the measured data pick-up MDA is preferably arranged within the system S in order to register the measured data on site. The measured data are conducted to a processor unit PRE where they are processed ~~and processed thereat~~. The processor unit PRE preferably comprises a neural network NN that, following training, suitably interprets further measured data registered by the measured data pick-up MDA. When there are indications that an action is to be implemented due to the measured data, an actuator AKT is initiated by the processor unit PRE to implement a predetermined action. The actuator preferably comprises at least one electrode that is directly driven by the processor unit PRE.

~~Let it thereby be noted that the~~ the processor unit is arranged in the system S', as indicated in Figure 1 on the basis of the broken line and the appertaining designation of the system S'.

The system S preferably comprises the measured data pick-up MDA and/or the actuator AKT in order to respectively assure a direct access of the measured data pick-up MDA to the measured data and of the actuator AKT to the system.

Figure 2 shows a differently constructed actuator AKT 2. ~~Via the interface 201, this~~ This actuator AKT2 likewise receives a signal from the processor unit PRE via the interface 201 that informs a computer R, which is part of the actuator AKT2, that a predetermined action is to be implemented. ~~Further,~~ Furthermore an energy store BT is provided in the actuator AKT2; ~~this~~ this. energy store BT, controlled by the computer R, ~~applying~~ applies energy to the electrodes EL1 and EL2 in a suitable way. The computer R of the actuator AKT2 ~~thereby~~ controls the interface IF in order to preferably determine amplitude and frequency of the energy applied to the electrodes EL1 and EL2.

Figure 3 shows steps of the method implemented by the processor unit PRE.

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A neural network NN is trained in a step 301. To this end, measured data of a suitable scope are prescribed in order -- following the training -- to be able to make a statement as to whether new measured data indicate an abnormality of the system. After the end of the training, an information flow (see [1] or [2]) is evaluated on the basis of current data in a step 302. An abnormality of the system can be indicated on the basis of this information flow before the occurrence of this abnormality. The abnormality is predicted in a step 303; an action that opposes an occurrence of the abnormality is implemented in a step 304. Subsequently, a branch is preferably made to the step 302.

Two applied examples follow, ~~these illustrating~~ that illustrate the possibilities of a prediction of an abnormality.

Application 1: Electrocardiogram (ECG) Data

One application relates to the possible prediction of a fibrillating heart. The abnormality occurs when ~~is comprised therein that~~ the heart beats nearly chaotically.

ECG measured data are inventively employed in order to learn the dynamics of a heart of a patient (the training phase of the neural network NN). ~~It should thereby be noted that the~~ The dynamics of the heart vary greatly dependent, for example, on the time of day and the activity in which a person is engaged at a particular ~~at the~~ moment. Invariable quantities (prediction quantity) that significantly describe the dynamics of the heart of a person ~~the person~~ despite great variation are ~~should~~ nonetheless ~~be~~ determined. A variation of the prediction quantity enables the prediction of an abnormality of the heart. A control mechanism that restores the normal heart rhythm is started upon recognition of the abnormality.

The prediction quantity represents an imaging of a sudden variation of the complexity of the dynamics, and the actuator is realized in the form of an electrode that delivers small electrical pulses to the heart.

Application 2: Electroencephalogram (EEG) Data

The brain, e.g. a human brain ~~preferably the human brain,~~ is another dynamic system. When it is assumed that EEG measured data represent brain activity, one task is to suitably interpret the signals and potentially link predetermined measures to them. An ~~thereto. Thus, an~~ epileptic attack is characterized by a synchronous firing of a group of neurons that are arranged centered around a mid-point. This synchronism reduces the complexity of the dynamics of the brain and is indicated by EEG measured data. In contrast to this ~~thereto,~~ the normal condition, ~~i.e.~~ the normally working brain, represents a condition of irregularly firing neurons.

The early recognition of an epileptic attack becomes possible by determining a continued simplification of the dynamics of the brain. The actuator for restoring the normal condition has the job of opposing this synchronism that is apparently responsible for the epileptic attack. This preferably occurs by applying a field, as explained in greater depth below.

The ~~We shall turn to the~~ second applied example for avoiding an epileptic ~~attack below for further-reaching comments~~. INS A16

The Dynamic Prediction Quantity

The idea is comprised in the expansion of the statistical approximation according to ~~[2]~~ Schittenkopf for detecting a Markov character in which a given empirical time row is inherent. One objective is to separate a deterministic part ~~form~~ from a stochastic part of a dynamic system in the ~~surround of the~~ area of statistical test theory in that the information flow of the system is analyzed. The statistical development of the dynamics is tested against a hierarchy of zero hypotheses that correspond to non-linear Markov processes with increasing order n. These processes are divided into a deterministic part and a stochastic part in the following way:

$$x_t = f(x_{t-1},\ldots,x_{t-n}) + u \qquad (1),$$

~~whereby~~ where u indicates an additive noise distributed according to Gauss with the variance σ^2, x_t indicates a measured datum at the time t and $f(x_{t-1},\ldots,x_{t-n})$ indicates a deterministic part.

The Markov process with the order n is defined by the conditioned probability densities thereof

$$p(x_t \mid x_{t-1},\ldots,x_{t-n}) \propto \exp\left(-\frac{\left[x_t - f(x_{t-1},\ldots,x_{t-n})\right]^2}{2\sigma^2}\right) \qquad (2).$$

The deterministic part is implemented by a neural network NN that is trained according to the maximum likelihood principle ~~[4]~~ Insall applied to the probability densities according to Equation (2). The stochastic part u is described by noise distributed according to Gauss, ~~whereby~~ where the variance σ^2 is referred to a defined, mean last ~~[sic]~~ quadratic error. In other words, the zero hypotheses contain not only the order of the Markov process but also an actual deterministic structure. When a chaotic condition is present, thus, the order of the accepted zero hypothesis is the EED (effective embedding dimension). This approach opens up a method for determining the EED, whereas temporary measured data are modelled parallel ~~thereto~~ to it.

This approach also allows a strict expansion of the concept of ED (embedding) when a chaotic condition prevails. The express determination of the deterministic part is a method for filtering the noise out of the time row.

The zero hypothesis is implemented with a method described in ~~[2]~~ Schittenkopf.

Deco Schittenkopf

As known from ~~[1]~~ and ~~[2]~~, an information flow, i.e., a non-parametric criterion of a predictable development, is used as a discriminating statistic. A significance test is ~~thus~~ implemented for every point in time to be predicted, where ~~whereby~~ the zero hypothesis (i.e., a given assumption that is to be checked) is only accepted when the significance test is met for all quantities of the point in time to be predicted.

Analysis of Human Epilepsy Attacks

As described above, one application of the invention is represented by the analysis of EEG measured data in order to prevent an epileptic attack. One goal is to test, in this analysis ~~thereby to test~~ whether a dynamic classification of the measured data for time windows of different size can be used as prediction quantities in order to predict an epileptic attack. In particular, two prediction quantities are recited:

a) The "reminder" of the underlying dynamics, i.e., the EED (see the above comments);

b) a non-parametric criterion for a predictability, defined by the integration of the information flow.

The approach presented here does not assume that the underlying dynamics are chaotic (even if they could be); rather, the emphasis lies on the time span preceding the epileptic attack in order to define a prediction quantity for the epileptic attack that is based on the dynamics of the system.

Control of the Epileptic Attack

An epileptic attack can be suppressed in that a constant electrical field is supplied to the regions that are affected by the epileptic attack (see ~~[5]~~). INS A12

According to an assumption that the normal condition of the brain is marked by chaotic dynamics, an epileptic attack is expressed by a drastic simplification of the dynamics in the brain. The epileptic attack is countered in that the reduction of the dynamics, i.e., the synchronicity is, as described above, opposed in that a noise is supplied to the system, ~~the brain in this case~~. the brain, in this case.

The delivery of this noise is preferably generated by applying an electrical field or a magnetic field in the immediate environment of (as close as possible to) the location of the action. Electrodes for generating an electrical field or coils for generating a magnetic field are preferably employed for this purpose. The synchronously firing neurons in the epileptic attack have their synchronicity disturbed by the electrical and/or magnetic field; a (seemingly) chaotic firing of the neurons is re-established in the brain~~;~~ and the epileptic attack has thus been averted.

It is ~~thus~~ fundamentally important that a suitable reaction is carried out in response to an abnormal behavior of a dynamic system, ~~whereby~~ INS A13 the abnormal behavior is detected with a prediction quantity. ~~Dependent of~~ Dependent on the field of employment, this reaction ~~is comprised~~ may be, for example, ~~in~~ generating a chaotic field or in generating a regular field. This action, which is implemented by the actuator, is dependent on the respective field of employment. What the various versions of the method respectively have in common is a dynamic learning, ~~whereby~~ in which a significant abnormality is allocated to a prediction quantity and this prediction quantity enables a detection of an impending abnormality. ~~It is thereby expedient to~~ the methods then implement a suitable action with the actuator within a predetermined time interval preceding the occurrence of the abnormality (e.g. of the epileptic seizure or of the chaotically beating heart). The prediction quantity thus enables the recognition of an abnormality before ~~this~~ the abnormality actually occurs.

Since the entire system changes over a longer time span in view of its dynamically normal property, an adaption of the originally learned dynamic system is ~~expedient~~ necessary. It is important to define the prediction quantity in that the data significantly characterizing an abnormality are imaged from the entire dynamic system in the prediction quantity. A prediction of the abnormality can thus ensue even given a dynamic system subject to great fluctuations, for example, a heart that is subjected to ~~the greatest~~ a great variety of stresses, ~~whereby~~ and where one of these stresses does not necessarily indicate an abnormality.

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The following publications were cited in the framework of this document:

[1] G. Deco, C. Schittenkopf and B. Schürmann, "Determining the information flow of dynamical systems from continuous probability distributions", Phys. Rev. Lett. 78, pages 2345-2348, 1997.

[2] C. Schittenkopf and G. Deco, "testing non-linear Markovian hypotheses in dynamical systems", Physica D104, pages 61-74, 1997.

[3] J. Herz, A. Krogh, R. Palmer, "Introduction to the Theory of neural computation", Addison-Wesley, 1991.

[4] G. Deco, D. Obradovic, "An Information-Theoretic Approach to Neural Computing", Springer-Verlag, 1996, Chapter 7.2.

[5] B. Gluckmann, E. Neel, T. Netoff, W. Ditto, M. Spano, S. Schiff, "Electric field suppression of epiletiform activity in hippocampal slices", Journal of Neurophysiology 76, pages 4202-4205, 1996.